bCharge: Data-Driven Real-Time Charging Scheduling for Large-Scale Electric Bus Fleets

Guang Wang¹, Xiaoyang Xie¹, Fan Zhang², Yunhuai Liu³, Desheng Zhang¹

guang.wang@rutgers.edu

Rutgers University¹, SIAT², Peking University³
Outline

• Introduction
• Dataset & Analysis
• Data-Driven Model
• Evaluation Results
• Discussion
Introduction

• Air Pollution

PM2.5 Source of Beijing

- vehicle emissions: 31%
- industrial production: 14%
- fire coal: 14%
- dust: 23%
- others: 18%

• Energy Security

China Oil Consumption (Thousand Barrels Per Day)

tripled
Introduction

- Electric private vehicle
- Electric taxi
- Electric truck
- Electric bus
- Electric Uber

**Long Charging Time**
- Slow charging: 8 hours
- Fast charging: 2 hours

**Different Charging Patterns**
- Private vehicle: charge at home
- Taxi: reduce time by fast chargers
- Bus: reduce cost
Question & Challenge

• Can we reduce the charging cost of large-scale e-bus fleets considering real-world factors (e.g., traffic conditions, time-varying electricity pricing), combined with the real-time requirement, (i.e., timetable guarantee)?

• Challenges:
  • Hard to get large-scale data
  • Data clean and analysis
  • Real-world constraints
Opportunity

E-bus News

Shenzhen Completes Switch To Fully Electric Bus Fleet. Electric Taxis Are Next.

January 1st, 2018 by Steve Hanley

Shenzhen, located just north of Hong Kong, is home to BYD, which happens to build electric vehicles, including buses. With a population approaching 12 million, Shenzhen has a lot of buses — 16,359 of them, to be precise — and as of this moment, every one of them is electric. Nicolas Zart told us in last month on the city’s push to convert its bus fleet to electricity. Now the conversion is complete.

Data Collection

Data Utilization

DATA SCIENCE FOR SOCIAL GOOD

THE SMART CITY

OPEN DATA
Contribution

• **bCharge: First data-driven e-bus**
  - over 2 TB e-bus GPS, 16,000 e-buses, 370 charging stations

• **Design**
  - Markov Decision Process based scheduling algorithm
  - Contextual factors, e.g., time-varying electricity pricing
  - Real-time requirement, i.e., timetable guarantee

• **Implementation & Evaluation**
  - Real-world streaming data
  - 23.7% charging cost reduction

• **Lessons Learned**
  - Real-world issues, limitation, etc
Outline

• Introduction

• **Dataset & Analysis**

• Data-Driven Model

• Evaluation Results

• Discussion
# Dataset

## Bus GPS Data

<table>
<thead>
<tr>
<th>GPS Dataset</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>07/2014-06/2018</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># E-Bus</td>
<td>16,000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GPS Data Size</td>
<td>2.75 TB</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># Records</td>
<td>10.1 billion</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

## Bus Fare Data

<table>
<thead>
<tr>
<th>Fare Dataset</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>07/2014-06/2018</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># E-Bus</td>
<td>16,000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fair Data Size</td>
<td>461 GB</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># Records</td>
<td>5.26 billion</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

## Bus Charging Station Data

<table>
<thead>
<tr>
<th>Station Dataset</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>01/2018</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># Station</td>
<td>371</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Station Data Size</td>
<td>3 KB</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># Charging Points</td>
<td>Over 5,000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

## Bus GPS Data

<table>
<thead>
<tr>
<th>plateID</th>
<th>lineID</th>
<th>longitude</th>
<th>latitude</th>
<th>time</th>
</tr>
</thead>
<tbody>
<tr>
<td>BSXXXXX</td>
<td>M4893</td>
<td>114.022901</td>
<td>22.532104</td>
<td>2018-01-14 00:00:04</td>
</tr>
</tbody>
</table>

## Bus Fare Data

<table>
<thead>
<tr>
<th>UserID</th>
<th>plateID</th>
<th>boarding time</th>
<th>lineID</th>
<th>Company</th>
</tr>
</thead>
<tbody>
<tr>
<td>U000001</td>
<td>SZXXXXD</td>
<td>2018-09-02 06:50:51</td>
<td>K578</td>
<td>Shenzhen Bus</td>
</tr>
</tbody>
</table>

## Charging Station

<table>
<thead>
<tr>
<th>stationID</th>
<th>stationName</th>
<th>longitude</th>
<th>latitude</th>
<th>number of charging points</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>NB0005</td>
<td>113.9878608</td>
<td>22.55955418</td>
<td>40</td>
</tr>
</tbody>
</table>
# Operating Pattern

- **Bus**: 16,359
- **Bus Line**: 1,400
- **Bus Station**: 5,562
- **Bus Passenger**: 5 M

### Operating Pattern

- **Operating Pattern**: 12/12/18

#### Key Metrics:

- **93%** e-buses have at least one charge
- **32%** e-buses have at least twice
Charging Pattern

Spatial Distribution of Shenzhen E-bus Charging Network (Jan. 2018)
Cost Pattern

Off-peak hours

Flat hours

Peak hours

Electricity Usage

Charging Cost Distribution

Time-Varying Electricity Pricing
Field Study

E-buses in Shenzhen

E-bus Charging Station in Shenzhen

Charging Point
Outline

• Introduction

• Dataset & Analysis

• Data-Driven Model

• Evaluation Results

• Discussion
Key Idea

- **Objective**

\[
F_s - C_c = \sum_{t=24h} \sum_{n=1}^{N_{eb}} (F_n^t - R^t \cdot C_n^t)
\]

Collected fare \hspace{1cm} # of e-buses

maximize Profit = minimize Charging cost

- **Key Idea**

- E-buses to serve other bus lines
- More charges in off-peak hours
- Timetable guarantee

- Fare of n\textsuperscript{th} bus
- Consumed electricity

Electricity rate

 Far of n\textsuperscript{th} bus
MDP

MDP is a 5-tuple \((S, A, T, R, \beta)\)

- \(S\) is a set of states
- \(A\) is a set of actions
- \(T\) is a state transition matrix
- \(R\) is a reward function
- \(\beta\) is the discount factor
bCharge Scheduling

- Serving Current line & < Full SOC
- Serving other lines & < serving Current lines

Full SOC

Charging at this terminal
< mandatory charging threshold

Cost for charging

Staying at the terminal not charge

Serving a New line

Transition probability

Revenue

Going back to the Original terminal

Transition probability

12/12/18
Outline

• Background

• Dataset & Analysis

• Data-Driven Model

• Evaluation Results

• Discussion
Evaluation

• Evaluation Data
  ▪ One week data from Jan. 2018

• Baselines
  ▪ Ground Truth
  ▪ Earliest Deadline First (EDF)

• Evaluation Metrics
  ▪ Temporal Distribution
  ▪ Electricity Usage
  ▪ Charging Cost
  ▪ Spatial Distribution
Temporal & Usage

Temporal Distribution

12.8% Reduction
Decrease: 701 MWh /day
Charging Cost

23.7% Reduction
Decrease: $106,870 /day
Decrease: $39 million /year
Spatial Distribution

3-6: from 66% to 73%, 7% improvement
Outline

• Introduction
• Dataset & Analysis
• Data-Driven Model
• Evaluation Results
• Discussion
Discussion

• Lessons Learned
  • More Buses vs. Effective Scheduling vs. More Charging Stations?
  • Implementation in Different Cities

• Impact & Generalization
  • Immediate Impacts: Cost Reduction for Shenzhen
  • Potential Impacts: Shenzhen Mode ➔ Other Cities
Conclusion

• **bCharge: First data-driven e-bus scheduling**
  - Using over 16,000 e-buses, 2 TB GPS, 370 charging station
  - Designing an MDP based, time-varying electricity
  - Implementing, real-time requirement, 23.7% reduction
  - Lessons learned

_data and more work_
@ https://www.cs.rutgers.edu/~dz220/

Thank you!
Q&A